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**Winter Binds, Summer Does Not: The Heat-or-Eat Trade-off across the Income
Distribution in South Korea**

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Abstract

This study examines how household energy and food budget shares respond to the mean and variability of seasonal temperature in South Korea, with attention to differences across the income distribution. Using nationally representative panel data from 2017 to 2021 and a survey-weighted fractional response model with district-level cluster-robust inference, we document an income-differentiated, seasonally asymmetric pattern of expenditure reallocation. In winter, lower-income households face a pronounced "heat-or-eat" trade-off: as conditions turn colder, they raise the energy budget share while cutting the food share, whereas higher-income households raise energy spending without reducing food. Modeling the interaction of temperature level and variability further reveals a threshold at which the most extreme winters cap the heating response and halt further food cuts, preserving a floor under minimal nutrition. In summer, by contrast, no comparable trade-off emerges for either group, so the squeeze on essential consumption is specific to winter rather than a generic response to temperature. The winter pattern is robust to within-household estimation and to inference based on a wild cluster bootstrap. These findings locate the energy–food margin within household consumption inequality and support season-specific, coordinated approaches to energy and food assistance.

Keywords: heat-or-eat; energy–food trade-off; energy poverty; consumption inequality; seasonal temperature; household expenditure

JEL: D12, Q41, Q54, I32, D11

1. Introduction

Household exposure to economic pressure is unequally distributed: resource-limited households, who devote the largest shares of their budgets to necessities, are also the least able to absorb recurring shocks to the cost of those necessities. One increasingly salient source of such pressure is climate. As global climate patterns become increasingly erratic, households worldwide must adapt their spending to cope with unpredictable weather conditions, and the burden of this adaptation falls unevenly across the income distribution.

A pressing concern is the impact of climate shocks—such as heatwaves, cold spells, and abnormal temperature fluctuations—on household energy demand and food consumption, particularly for resource-limited groups. These households, often situated in areas prone to climate-related hazards or vulnerable housing environments, are especially susceptible to energy price fluctuations (Randazzo et al., 2020). Additionally, households exposed to climate-related threats frequently face higher risks of food insecurity (Kroegeer 2023). Consequently, those affected by climate shocks may have to make difficult choices between spending on energy or food (Lee et al., 2020; Doremus et al., 2022). As climate change accelerates, understanding how households navigate these trade-offs—and why poorer households navigate them on far tighter margins—is critical for informing equitable and effective policy interventions.

South Korea offers a particularly relevant setting for these questions. Its energy pricing and distribution system, managed by entities such as the Korea Gas Corporation (KOGAS) and the Korea Electric Power Corporation (KEPCO), plays a crucial role in shaping household energy costs, particularly during extreme weather events (see Appendix A for additional details). Despite regulated energy prices that aim to stabilize household costs, energy suppliers have increasingly faced mounting financial pressure—a tension that intensified after 2022—due to the gap between market and regulated prices, sparking ongoing debates over energy reforms and price adjustments. In this environment, households—particularly lower-income groups—must navigate difficult spending choices under volatile climate conditions, and any rise in energy costs can severely compromise food consumption, intensifying the welfare consequences of these trade-offs.

While prior research has examined household responses to temperature, the following four questions remain open, and addressing them defines this paper’s contribution. First, the energy–food trade-off has received limited attention through the lens of seasonal temperature variability; we make that trade-off the explicit object of analysis. Second, because much of the literature emphasizes average climate conditions, we model the mean and the variance of seasonal temperature jointly. Third, the non-linear effects arising from the interaction between temperature level and variability remain less well understood; we estimate these interactions directly, recovering threshold effects that linear, mean-only models miss. Fourth, and central to this paper, we treat the energy–food margin as a question of consumption inequality, assessing how the trade-off differs across the income distribution and between seasons rather than as a uniform climate impact.

We hypothesize that lower-income households reduce food expenditures to accommodate rising energy costs, and that this trade-off is more pronounced in winter than in summer—reflecting the larger heating burden and greater wintertime temperature variability that Korean households face—rather than being a generic response to temperature stress in either season. To test this, we apply a fractional response model to nationally representative household panel

data from the Korean Labor and Income Panel Study (KLIPS) for the period 2017 to 2021, controlling for food and energy prices, sociodemographic factors, and regional climate conditions, and incorporating interaction terms between temperature mean and variability. To the extent that this seasonal squeeze on essential consumption is borne disproportionately by poorer households, it constitutes a recurring, climate-driven form of consumption inequality—one that conventional, annual-average measures of household welfare do not capture. By modelling these compounded effects of climate stress on household consumption behavior, the study offers new insights for both anti-poverty and climate adaptation policy.

The remainder of this paper is organized as follows. Section 2 reviews the relevant literature. Section 3 outlines the theoretical framework and empirical methodology. Section 4 presents the data and summary statistics. Section 5 reports the estimation results. Section 6 concludes with policy implications.

2. Literature Review

Understanding the main drivers of household energy demand and spending has long been a topic of interest in policy analysis. Rising prices in recent years and expected future price increases necessitate ongoing studies on the factors affecting energy demand. Residential energy is used for necessities such as heating and cooking, as well as for leisure activities and production purposes like working from home (Meier et al., 2013). Price and income are widely suggested as the main determinants of residential energy consumption, with demand for these services tending to increase with income (Cayla et al., 2011; Kostakis 2020; Belaid and Rault 2021) and decrease with price (Bechlioulis and Brissimis 2021). Surging energy prices can affect household energy consumption differently due to unequal income distribution (Guan et al., 2023).

Other studies have shown that household electricity consumption is related to sociodemographic characteristics such as age, education level, gender of the household head, and household size (Kostakis 2020; Frandel et al., 2019). Additionally, energy expenditures can vary due to housing characteristics, such as housing type and property tenancy (Belaid and Rault 2021; Meier and Rehdanz 2010).

Several studies have highlighted the importance of climate conditions and environmental factors as determinants of residential energy consumption (Zhang et al., 2020; Liddle and Huntington 2021; Li 2018). While climate change may affect electricity demand through heating and cooling needs, extreme temperatures have a stronger effect than moderate ones (Silva et al., 2020). Furthermore, energy demand is notably more responsive to weather changes in the residential sector compared to the commercial sector (Fazeli et al., 2016). Notably, most of this literature characterizes the temperature–energy relationship through average or threshold-exceedance measures, leaving the role of within-season temperature variability—as distinct from the level—largely unexamined (e.g., degree-day-based building energy studies such as Berardi and Jafarpur 2020).

A smaller but growing body of work suggests that the variability of temperature, not only its average level, matters for household outcomes. Unpredictable conditions raise adjustment costs, complicate planning, and increase exposure to tail events such as cold snaps and heatwaves (Cawthorne et al., 2021; Larsen et al., 2020). Cawthorne et

al., (2021) find that interannual temperature variability explains a substantial share of seasonal residential electricity demand, net of population and economic growth, while Larsen et al., (2020) show that heating and cooling demand changes computed from temperature extremes are considerably larger than those implied by shifts in the mean alone. Consistent with this emphasis on the tails, we follow Coibion et al., (2024) in weighting the extremes of the seasonal temperature distribution when constructing our temperature moments. Moreover, the effect of cold or heat may itself depend on how variable conditions are, generating threshold and compounded effects that linear, mean-only specifications cannot capture (Aroonruengsawat and Auffhammer 2011; Longden 2025). These two features—variability as a distinct moment, and its interaction with the mean—motivate the joint modelling of mean and variance adopted in this paper.

Household spending patterns on food need to be examined from a different perspective than those on energy. While energy consumption is assumed to be of consistent quality across income levels, food choices vary significantly in quality. In this context, food quality refers to diet quality, often implying less processed, fresher, and healthier foods. High expenditure on food can indicate either purchasing a large quantity of low-quality (e.g., low nutrient, highly processed, or frozen ready meals) and inexpensive food or a small quantity of high-quality and often more expensive food, such as organic produce. Therefore, it is difficult to generalize and interpret changes in the amount spent on food due to climate shock as either a positive or negative sign for the household budget.

Studies highlight that higher socioeconomic status (SES) households are more likely to purchase and consume healthier foods (Venn et al., 2017). Compared to low-SES groups, high-SES groups often have better knowledge, greater access to resources for healthy living through financial, social, and community capital, and a higher ability to pursue healthy eating behaviors. Despite being in the high-SES group, many households cite time constraints and long working hours as obstacles to maintaining a healthy diet. Individuals who feel rushed while preparing meals are less likely to follow dietary recommendations (Restrepo and Zeballos 2020).

The impact of climate on food spending patterns tends to be more indirect compared to energy consumption. The most prevalent effect is through income and price changes. For example, extreme climate events can lead to spikes in food prices (Erdogan et al., 2024), which can subsequently impact household food consumption behavior through price and budget constraints (Yüksel et al., 2021). Insufficient income or price shocks become even greater barriers to accessing a healthy diet in the face of extreme climate events, potentially expanding into a broader food insecurity issue (Penne and Goedemé 2021).

A critical aspect of this research is the ‘energy-food’ trade-off in household expenditure in the context of temperature variability. Under significant temperature changes, households are expected to experience increased spending on health, electricity, and food. While higher-income households can more easily absorb the rising cost of necessities with minimal impact on other expenditure areas (Schanzenbach 2016), the overall contraction in income would limit low-income households’ ability to cope with the residual costs of temperature variability and to adapt, increasing their risk of falling below the poverty line (EESC 2023).

Increased energy costs, particularly in response to mean and variance of temperature changes, often compel households to reduce spending on other necessities like food and medical care (Cullen et al., 2004; Bhattacharya et

al., 2003). This trade-off is more pronounced in lower-income and older households (Beatty et al., 2014; Doremus et al., 2022), indicating a socioeconomic gradient in vulnerability to temperature fluctuations. Importantly, much of this “heat-or-eat” evidence is drawn from cold-season heating costs in temperate or high-latitude settings, including several of the studies cited above; the symmetric question of whether summer cooling costs force an analogous “cool-or-eat” reallocation is far less studied, particularly outside the United States and Europe. One of the few studies to link warm-climate temperature stress to household energy hardship in a developing-Asia setting is Feeny et al., (2021), who find that temperature shocks raise energy poverty in Vietnam. Relatedly, in a high-heat region of the United States, Cong et al., (2022) show that lower-income households tolerate substantially higher outdoor temperatures before turning on cooling, revealing an income gradient in summertime cooling that conventional metrics miss. This asymmetry in the existing evidence motivates our two-season design, in which summer serves as a deliberate analytical contrast to winter rather than an afterthought.

Viewed through this lens, the energy–food trade-off is not only a climate-adaptation question but a dimension of household consumption inequality. A growing literature on energy poverty documents that lower-income households devote disproportionate budget shares to energy and are forced to ration essential services when costs rise (Fry et al., 2023; Gupta et al., 2020), with this rationing intensifying under temperature stress (Feeny et al., 2021). Because such households allocate the largest shares of their budgets to necessities (Engel’s Law; Anker 2011) and hold the thinnest buffers against cost shocks (Schanzenbach 2016; EESC 2023), a given climatic shock translates into a larger and more welfare-relevant reallocation for them than for richer households. Yet the energy-poverty literature typically measures exposure with annual or average-condition indicators (Cong et al., 2022), and rarely distinguishes how the squeeze varies across seasons or with the variability of temperature, as opposed to its level. By characterizing how the trade-off differs across the income distribution and between winter and summer, this study connects the climate-and-consumption literature to the analysis of consumption inequality and poverty at the household level.

3. Methodology

3.1 Theoretical Framework

The theoretical foundation for understanding why households may change energy expenditures in response to temperature change is based on Auffhammer and Mansur (2014). Define the utility function for a household as follows:

$$U = U(E, F, Y; T_0), \quad (1)$$

where E is a vector of energy sources, F is a vector of food consumption¹ that indirectly affects energy expenditure by budget constraints. Specifically, as households face increased energy costs to maintain comfortable indoor temperatures, they may need to adjust their spending on food, leading to a potential trade-off between energy and food

¹ This could include the quantity and quality of food consumed, frequency of dining-outs or eating at home, or any other food-related expenditures.

consumption. Y represents all other composite goods, and T_0 denote the current distribution of outdoor temperature influencing household utility.

The household will maximize utility by choosing E, F and Y , subject to their income (M) and the prices of energy (P_E), food (P_F), and other goods (P_Y). The maximization problem is formalized as:

$$\max_{E,F,Y} U(E, F, Y; T_0) \text{ s.t. } P_E E + P_F F + P_Y Y \leq M, \quad (2)$$

where we denote the choices that maximize utility given the current outdoor temperature as $E^*(T_0)$, $F^*(T_0)$, and $Y^*(T_0)$.

A household's utility is derived from consuming $E^*(T_0)$ and $F^*(T_0)$, where energy consumption directly linked to maintaining stable interior temperature, T_{in} , and food consumption plays a role in helping the household cope with and adapt to varying temperatures. The energy needed to maintain the desired interior temperature T_{in} is determined by the difference between the interior temperature and the external temperature T : $E = E(|T_{in} - T|)$.

Climate change alters the probability $f(T)$ of experiencing specific temperature T on any given day, causing a shift in the temperature distribution from T_0 to T_k . In response to these changes, a household might allow its interior temperature to fluctuate with the external temperature. However, if the household opts to keep the interior temperature constant, the resulting change in expenditures can be used to address welfare effects of climate change. The change in expenditures represents the welfare effect of these temperature-induced adjustments.

$$\Delta W = P'_E \cdot (E^*(T_k) - E^*(T_0)) + P'_F \cdot (F^*(T_k) - F^*(T_0)) \quad (3)$$

where P'_E and P'_F represent the marginal prices of energy and food, respectively².

3.2 Empirical Model

This section details the empirical model used to assess how households adjust their spending on energy and food in response to temperature changes, particularly to determine whether there is a trade-off between "heating" and "eating" during colder periods, and "cooling" and "eating" during hotter periods. Our empirical model specification incorporates the effects of both the mean and variance of temperature on household spending, leveraging the fact that we have measures of both the first and second moments of the temperature distribution during summer and winter:

$$Y_{ijt}^{(k)} = \gamma_{0ijt} + \gamma_1 T_{\mu,jt}^s + \gamma_2 T_{\sigma,jt}^s + \gamma_3 T_{\mu,jt}^{w*} + \gamma_4 T_{\sigma,jt}^w + \gamma_5 (T_{\mu}^s \times T_{\sigma}^s)_{jt} + \gamma_6 (T_{\mu}^{w*} \times T_{\sigma}^w)_{jt} + \theta M_{ijt} + \delta^{(k)}(P_{j,t}^k - P_{j,t-1}^k) + \zeta X_{ijt} + \epsilon_{ijt}^{(k)} \quad (4)$$

where the dependent variable is the budget share of household expenditure on spending category k (including food and energy) in total household expenditure. Subscript i denotes individual households, j denotes the region (si-gun-

² In this context, the primes on P_E and P_F denote that these are not static prices but are subject to change, particularly in response to changes in external factors, including temperature.

gu), and t denotes time (year). $T_{\mu,jt}^s$ and $T_{\sigma,jt}^s$ represent the mean and variance of summer temperatures, while $T_{\mu,jt}^{w*}$ and $T_{\sigma,jt}^w$ represent those for winter³. The winter mean temperature values were multiplied by -1 to facilitate interpretation, transforming colder temperatures into larger positive values and warmer temperatures into smaller negative values. The coefficients $\gamma_1, \gamma_2, \gamma_3, \gamma_4$ represent the absolute change in the budget share of household expenditure on a given category (e.g., energy or food) for a 1-unit change in the respective temperature measure. The coefficients γ_5 and γ_6 are the coefficients on the summer and winter mean-by-variance interaction terms, respectively; the remaining terms capture household income, the within-category price change, and the household controls.

M_{ijt} denotes annual household income, and P_{jt}^k is the price index for spending category k , with the first difference ($P_{jt}^k - P_{j,t-1}^k$) capturing short-term price changes and their effects on household spending. X_{ijt} is a vector of control variables, including household characteristics such as age, household size, education, and tenure status, as well as year and region⁴ fixed effects. $\epsilon_{ijt}^{(k)}$ is the error term. The model includes interaction terms between the mean and variance of temperature, allowing us to examine how the effects of colder or warmer conditions change when temperature variability increases⁵. We employ a fractional probit model to estimate the effects on energy and food expenditure shares, accounting for the bounded nature of the dependent variable $[0,1]$.

All point estimates apply the KLIPS 09-integrated-sample household longitudinal weight, so that estimates are representative of the target population over the 2017–2021 waves. For inference, we cluster standard errors at the si-gun-gu (district) level. This is dictated by the structure of the key regressors: the temperature moments are constant across all households within a district-year, so the regressor of interest varies only at the district level, and the resulting within-district error dependence is the first-order threat to valid inference. Because the analytic sample contains roughly thirty households per district-year (median twenty-three) across more than two hundred districts, each cluster is well populated, and weighting (for representativeness) and clustering (for inference) are applied jointly rather than as substitutes. We incorporate the survey design through this longitudinal weight and through district-level clustering rather than through a fully specified stratum-and-PSU variance estimator; because the temperature regressors vary only at the district level, district clustering is at least as conservative as clustering on the original sampling units, which are nested within districts.

As a robustness check, we also cluster at the coarser si-do level (sixteen clusters); because conventional cluster-robust inference is unreliable with so few clusters, we assess significance with a wild cluster bootstrap. Appendix D

³ For the calculation of mean and variance of temperature in our analysis, we applied a triangular distribution to give greater weight to extreme temperature events (such as heatwaves and cold spells), following the approach outlined in Coibion et al. (2024). This method emphasizes the tails of the distribution, where temperature extremes occur, providing a better representation of their impact on household expenditures.

⁴ We categorized the regions into four groups based on the Köppen–Geiger climate classification map of South Korea as outlined in Pradhan et al. (2024). The classification divides the regions as follows: (1) Humid continental climate (Dwa/Dwb): Seoul, Incheon, Gyeonggi, Gangwon; (2) Humid subtropical climate (Cwa): Daegu, Gyeongsangnam-do, Gyeongsangbuk-do, Chungcheongbuk-do, Chungcheongnam-do; (3) Oceanic climate (Cfb): Jeollanam-do, Jeollabuk-do, Gwangju, Jeju; and (4) Coastal climate (Cfa/Cwa): Busan, Ulsan. Climate-based region classification can reduce omitted variable bias and improve model fit by better capturing unobserved climate effects compared to traditional regional divisions.

⁵ For example, a positive interaction coefficient between cold temperatures and temperature variance suggests that as variability increases, the effect of colder conditions on energy (or food) spending intensifies, likely due to increased heating needs during fluctuating conditions. A negative coefficient indicates that colder conditions mitigate the impact of variability, making households less sensitive to temperature fluctuations.

reports two such checks—a within-household (household and year fixed-effects) linear specification and the si-do wild cluster bootstrap—both of which preserve the winter heat-or-eat pattern. Goodness of fit for each specification is summarized in Appendix Table A1, which reports the number of observations, the number of district clusters, and a deviance-based pseudo- R^2 alongside the full coefficient vector.

The total impact for each season on household budget share can be represented as the sum of the marginal effects for mean and variance, incorporating both the direct and interaction effects of the temperature variables. To account for the uncertainty in temperature impacts on household spending, we use temperature distributions based on historical data. For each region and year, we calculate the probability density function (PDF) weighted mean and variance to capture the expected impact of temperature fluctuations on household spending. The combined marginal effect of the mean and variance on household spending for summer (T^s) and winter temperatures (T^w) is given by:

$$\frac{\partial Y}{\partial T_\mu^s} = \gamma_1 + \gamma_5 \cdot E[T_\sigma^s] \quad (5)$$

$$\frac{\partial Y}{\partial T_\sigma^s} = \gamma_2 + \gamma_5 \cdot E[T_\mu^s]$$

$$\frac{\partial Y}{\partial T_\mu^{w*}} = \gamma_3 + \gamma_6 \cdot E[T_\sigma^w] \quad (6)$$

$$\frac{\partial Y}{\partial T_\sigma^w} = \gamma_4 + \gamma_6 \cdot E[T_\mu^{w*}]$$

where $E[T_\mu^s]$ and $E[T_\sigma^s]$ represent the expected values of the mean and variance of summer temperatures, respectively, and $E[T_\mu^{w*}]$ and $E[T_\sigma^w]$ represent the expected values of the mean and the variance of winter temperatures. This approach allows us to account for the full range of possible temperature outcomes and their probabilistic influence on household spending behavior.

4. Data

4.1 Descriptive Statistics

The analysis uses household data from 2017 to 2021, sourced from the Korean Labor and Income Panel Study (KLIPS) conducted by the Korea Labor Institute. The KLIPS data provides comprehensive socio-demographic and expenditure information for approximately 5,000 urban households in South Korea annually. This dataset includes average monthly living expenses, covering food (both at-home and dining out) and housing expenses (including rent and utilities such as electricity, water, and gas). For our analysis, we calculated home energy expenditure by subtracting rent from total housing expenses⁶.

On a survey-weighted basis, the monthly total household expenditure per capita averages about 868,500 KRW (roughly \$639), with about 75,300 KRW (\$55) allocated to home energy and 247,600 KRW (\$182) to food. This corresponds to approximately 8.7% of total spending on energy and 28.5% on food.

⁶ Given that water expenses are relatively low, calculating home energy expenditure by subtracting rent from total housing expenses is unlikely to cause significant inaccuracies.

Complementing this, daily temperature records from the Korea Meteorological Administration (KMA) provide the primary independent variables, measured as the daily mean temperature for each district (si-gun-gu). For each district-year we summarize summertime (June–September) and wintertime (November–February) temperatures by their mean and variance. Following Coibion et al., (2024), these moments are computed under a triangular weighting that places greater weight on the tails of the distribution, so that extreme events such as heatwaves and cold spells receive more emphasis. To ease interpretation, the winter mean is multiplied by -1 , so that larger positive values denote colder conditions. All households within a district share the same temperature reading; we account for this common component directly in estimation (see below). Because the KLIPS analysis sample is built at the household level, we also attach the survey’s 09-integrated-sample household longitudinal weight, which we use in all estimates.

Other explanatory variables include energy and food prices, demographics, education, and housing tenure status⁷, providing a comprehensive framework to assess expenditure shifts in response to temperature change and fluctuations. The price data are derived from Statistics Korea (KOSTAT) using Consumer Price Index (CPI).

In the analysis, we divide the sample based on the GPL status. This poverty threshold defined by the National Basic Livelihood Security System's guidelines which are set by the Ministry of Health and Welfare. The average monthly GPL was set at 1,729,352 KRW. This classification allows for an intricate exploration of how households across different socio-economic backgrounds adjust their spending in the face of adverse weather, offering insights into the economic impact of climate variations. Descriptive statistics are summarized in Table 1.

Table 1 Descriptive Statistics

Statistic	Mean	SD	min	max
Dependent (real household per capita expenditure, 10K KRW)				
Total household expenditure	86.85	43.18	0.00	1383.45
Home Energy (inc. electricity, gas, water)	7.53	5.00	0.00	112.24
Food (inc. at-home, dining out)	24.76	13.35	0.00	260.00
Independent				
<i>Temperature</i>				
Summertime mean	23.84	1.43	17.00	26.70
Wintertime mean	1.25	2.82	-9.35	8.60
Summertime variance	8.37	2.83	2.53	17.68
Wintertime variance	13.12	5.38	5.23	33.37
<i>Household</i>				
Monthly household income (1K KRW)	4.83	4.48	0.00	108.79
Age (% of HH over 65 years old)	0.27	0.44	0.00	1.00
Household size	2.69	1.30	1.00	8.00
<i>Education</i>				
Primary (eighth grade or less)*	0.23	0.42	0.00	1.00

⁷ Meier and Rehdanz (2010) suggest that differences in heating expenditures exist between owner-occupied and renter households.

Secondary (HS grad/two-year degree)	0.44	0.50	0.00	1.00
Tertiary (University or higher)	0.34	0.47	0.00	1.00
<i>Tenure status</i>				
Owned house*	0.62	0.49	0.00	1.00
Long-term lease (Jeonse ⁸)	0.18	0.38	0.00	1.00
Rent	0.15	0.36	0.00	1.00
<i>Price (2020=100)</i>				
Energy (CPI on electricity, gas, and water)	100.36	1.69	96.27	103.37
Food (CPI on agricultural goods)	98.12	6.17	89.44	110.05

Notes: Table values rounded to 1 decimal place. Data excludes missing or negative expenditure values. ‘*’ denotes reference category. HH = household head, CPI = consumer price index, KRW = Korean won.

4.2 Distribution of Household Spending by Income Level

Table 2 illustrates the distribution of household spending, comparing two groups categorized by their income relative to the Government Poverty Line (GPL): households in poverty ($I < 1$ GPL) and higher-income households (those earning over two times the GPL). The GPL is the baseline value for beneficiaries of the National Basic Livelihood Security Program (BLSP), with the average monthly GPL in our sample set at 1,729,352 KRW.

Households in poverty allocate the largest proportions of their budgets to energy and food, at 13.1% and 34.9% respectively, emphasizing the significant portion of their income consumed by basic needs. This high spending share reflects these households' vulnerability to fluctuations in energy and food prices, potentially limiting their capacity for other expenditures.

Among other expenses, households in poverty allocate the most significant share to household allowance (11.8%), followed by medical expenses (8.3%). The substantial spending on household allowance may be linked to East Asian “family” culture, where adult children often receive allowances from their parents or provide allowances to their parents as a means of maintaining family bonds (Takahashi et al., 2015). Other expenditures are distributed as follows: telecom (internet and phone bills) at 5.4%, public transportation at 4.3%, daily essentials at 4.1%, recreation at 3.8%, and vehicle maintenance at 3.7%. Within the poverty group, comparing the mean to the 90th percentile (i.e., higher earners within this group), the budget shares for energy, food, public transportation, daily essentials, and telecom decrease slightly, while the shares for medical expenses, education, durables, and vehicle maintenance increase. This suggests that as income rises within the poverty group, households modestly reduce the proportion of their budget devoted to basic necessities.

In contrast, higher-income households allocate a lower mean budget share to energy and food expenditures, at 7.6% and 27.0% respectively. Their spending patterns suggest that they have more disposable income and a broader array of spending choices beyond necessities. The 90th percentile figures being close to the mean indicates that even

⁸ ‘Jeonse’ is a unique Korean rental system where a large lump-sum deposit is made instead of monthly payments, usually returned at the end of the lease term.

as incomes increase within this group, the budget proportion for energy and food remains relatively stable. Overall, higher-income households allocate a smaller percentage of their budget to food compared to the poverty group, aligning with Engel's Law (Anker 2011). This trend is also observed for energy expenditures, though Engel's Law specifically pertains to food. The underlying principle is that as income rises, basic needs constitute a smaller portion of overall spending, allowing for a more diverse distribution of expenditures.

Similar to low-income groups, higher-income households spend a significant share of their budget on household allowances (17.9%). They also allocate substantial portions to education (11.1%) and vehicle maintenance (10.7%), which differs markedly from the spending patterns of low-income groups. However, at the 90th percentile, the share spent on education declines, while spending on other categories such as medical care, clothing, recreation, and durables increases. Nonetheless, education, vehicle maintenance, and allowances remain the top three expenditure categories after food.

Table 2 Mean Budget Shares by Income Group

	In poverty (< GPL)		Higher-income (2 GPL <)	
	Mean budget share	90 th percentile of the group	Mean budget share	90 th percentile of the group
Energy (inc. gas, electricity, water)	0.131	0.126	0.076	0.074
Food (inc. at-home, dining out)	0.349	0.342	0.27	0.266
Subtotal	0.480	0.468	0.346	0.340
<i>Other Expenses</i>				
Household allowance	0.118	0.117	0.179	0.178
Medical	0.083	0.088	0.023	0.024
Telecom	0.054	0.051	0.060	0.057
Public transport	0.043	0.042	0.025	0.024
Daily essentials	0.041	0.039	0.026	0.026
Recreation	0.038	0.039	0.049	0.054
Vehicle	0.037	0.040	0.107	0.109
Clothing	0.034	0.034	0.040	0.040
Education (inc. public, private)	0.014	0.016	0.111	0.107
Durables	0.007	0.008	0.014	0.016

Source: Author calculations.

5. Results

5.1 Temperature Effects on Energy vs. Food Spending

Table 3 presents the relationship between temperature variables and household energy and food expenditures across different income groups: the total sample, households below the poverty line (under GPL), and higher-income households (twice the GPL). While the total sample offers a broader perspective, the focus here is on how households across income groups reallocate consumption in response to temperature changes, highlighting the marginal effects of temperature variables and their interactions.

The results reveal a clear seasonal and socioeconomic asymmetry: the central finding is a robust winter “heat-or-eat” trade-off among lower-income households, while summer produces no comparable trade-off and serves as an instructive contrast.

In summer, higher mean temperatures modestly raise the energy budget share of lower-income households (marginal effect 0.020, significant at the 10% level); their food share also edges up (0.025), though this estimate is not statistically significant, rather than falling. Crucially, the two point estimates move in the same direction, so warmer summers place some upward pressure on both budgets without forcing a reallocation away from food. There is thus no summer “heat-or-eat” trade-off among vulnerable households: the squeeze that defines winter (examined below) is absent.

For higher-income households, neither the energy nor the food budget share changes significantly with summer mean temperature. Their consumption mix is essentially unresponsive to summer warmth, consistent with structural and technological buffers—such as energy-efficient housing and cooling systems—that limit any reallocation across essentials.

Taken together, the summer estimates show no statistically robust energy–food trade-off for either income group. This null result is itself informative: it establishes summer as the contrast against which the winter trade-off, examined next, stands out.

Winter conditions produce the paper’s central result. As conditions turn colder, lower-income households significantly raise their energy budget share (marginal effect 0.039, $p < 0.01$) while cutting their food share (-0.020 , $p < 0.10$), demonstrating a constrained capacity to meet heating and nutritional needs simultaneously. This is the structural “heat-or-eat” dilemma: when the budget constraint tightens in winter, vulnerable households substitute away from food to fund heating. The energy response is precisely estimated; the food reduction is robust in direction though estimated less precisely under district-level clustering.

Higher-income households also raise their energy budget share in colder winters (marginal effect 0.018, $p < 0.01$) but show no significant change in their food share, reflecting economic buffers that shield them from the trade-off. This divergence—poorer households cut food while richer households do not—is the income-inequality dimension of the result and the core contribution of the paper. Figure 1 illustrates this winter “heat-or-eat” asymmetry:

colder winters raise the energy budget share and reduce the food share among lower-income households, while higher-income households show no comparable food reallocation.

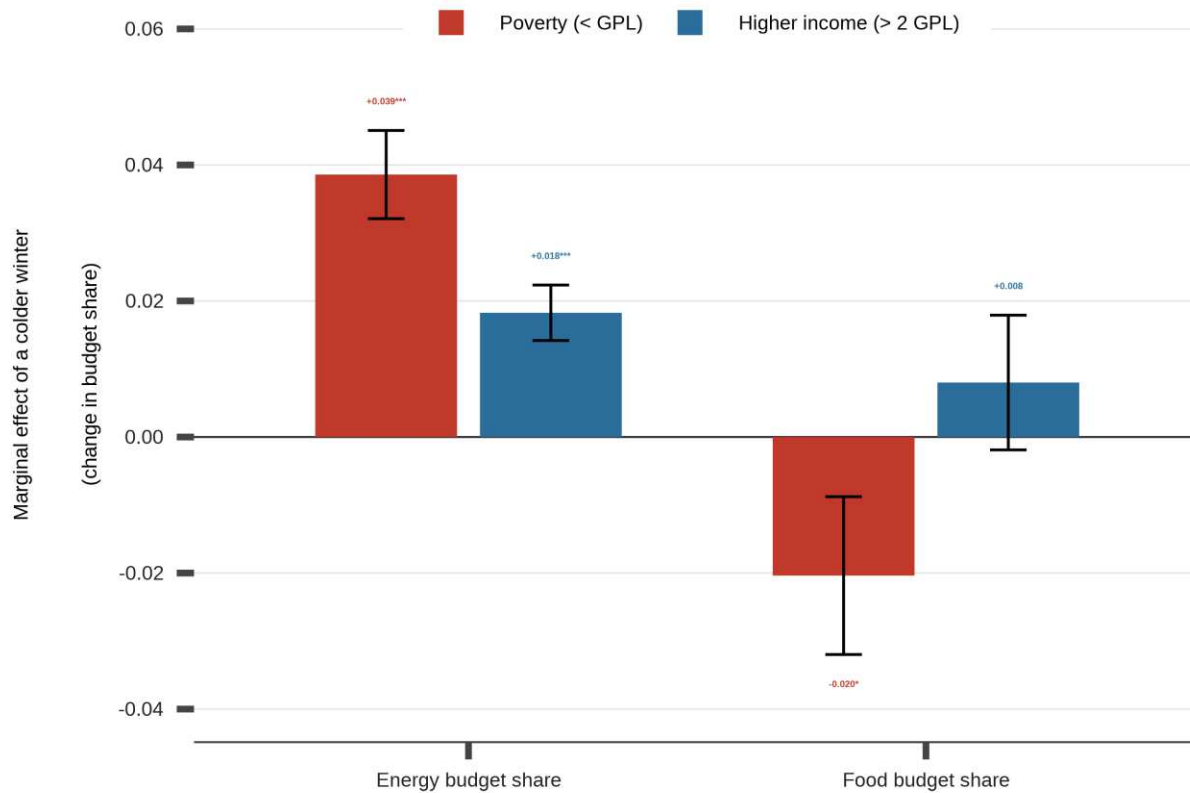


Fig. 1 Winter “heat-or-eat”: colder winters raise energy and cut food, but only for the poor

Note: Note: Survey-weighted marginal effects of a colder winter (a one-unit increase in the sign-reversed winter mean temperature) on the energy and food budget shares, by income group. Bars show point estimates; whiskers are standard errors clustered at the si-gun-gu (district) level. Red denotes lower-income households (below the Government Poverty Line, GPL); blue denotes higher-income households (above twice the GPL). ***, **, * denote significance at the 1%, 5%, and 10% levels.

Summer temperature variability does not generate a statistically robust adjustment in either budget share once standard errors are clustered at the district level: the summer-variance marginal effects are small and insignificant for both income groups. We therefore treat the summer-variability channel as suggestive at most, and do not draw trade-off conclusions from it.

Winter variability works in the same direction as the winter mean. Lower-income households continue to raise their energy budget share under more unstable winter conditions (marginal effect 0.008, $p < 0.10$), and their food share continues to point downward, though this reduction is not statistically significant. Higher-income households show smaller and largely insignificant adjustments, consistent with their ability to absorb winter volatility through discretionary rather than essential spending.

The interaction between the winter mean and winter variability sheds further light on these non-linear responses. For lower-income households the interaction term is negative for energy and positive for food, so greater winter variability dampens both legs of the trade-off rather than reversing it. As detailed in Section 5.2, this points to a threshold at which severely constrained households can no longer expand heating outlays and stop cutting food any further, preserving a floor under minimal nutrition.

Higher-income households exhibit no significant interaction effects, underscoring their ability to absorb combined climate stressors without compromising essential consumption. These findings emphasize that household adaptation is shaped by complex interactions between environmental and socioeconomic factors, producing differentiated consumption dynamics that linear models may overlook.

Table 3 Estimation Results on Temperature Effects on Energy vs. Food Spending

	Total		Poverty ("under GPL")		Higher Income ("2 times GPL")	
	Energy	Food	Energy	Food	Energy	Food
Summer mean	0.015 (0.013)	-0.002 (0.025)	0.038* (0.022)	0.007 (0.029)	0.014 (0.012)	0.015 (0.030)
Summer variance	0.021 (0.029)	-0.073 (0.049)	0.050 (0.045)	-0.057 (0.060)	0.044 (0.033)	-0.033 (0.060)
Winter mean	0.036*** (0.008)	-0.023 (0.015)	0.061*** (0.012)	-0.048** (0.019)	0.025*** (0.007)	-0.003 (0.017)
Winter variance	0.005** (0.002)	-0.004 (0.004)	0.006 (0.004)	-0.004 (0.005)	0.003 (0.002)	-0.006 (0.006)
Summer mean $\times$ variance	-0.001 (0.001)	0.003 (0.002)	-0.002 (0.002)	0.002 (0.003)	-0.002 (0.001)	0.001 (0.003)
Winter mean $\times$ variance	-0.001** (0.000)	0.001* (0.001)	-0.002*** (0.001)	0.003** (0.001)	-0.001 (0.000)	0.001 (0.001)
Year	Yes	Yes	Yes	Yes	Yes	Yes
Region	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R ²	0.320	0.128	0.206	0.072	0.176	0.061
N	23,562	23,562	6,851	6,851	10,551	10,551
Marginal effects at mean						
Summer Mean:	0.007 (0.007)	0.020 (0.013)	0.020* (0.011)	0.025 (0.015)	-0.001 (0.008)	0.025 (0.015)
Summer Variance:	-0.005 (0.004)	-0.002 (0.007)	-0.008 (0.005)	-0.000 (0.010)	-0.005 (0.003)	-0.003 (0.007)
Winter Mean:	0.024*** (0.004)	-0.006 (0.009)	0.039*** (0.006)	-0.020* (0.012)	0.018*** (0.004)	0.008 (0.010)

Winter Variance:	0.006**	-0.005	0.008*	-0.006	0.004	-0.007
	(0.002)	(0.004)	(0.004)	(0.005)	(0.002)	(0.006)

Notes: Estimates from survey-weighted fractional probit models (quasi-binomial GLM, probit link) using the KLIPS 09-integrated-sample household longitudinal weight. Standard errors (in parentheses) are clustered at the si-gun-gu (district) level (218 clusters). The dependent variable is the budget share of household expenditure on the indicated spending category. All models include year and region fixed effects and the controls described in Section 3.2. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Full coefficient estimates are reported in Appendix Table A1.

5.2 Combined Effects of Temperature Mean and Variability on Energy and Food Spending

Building on the marginal effects from Section 5.1, Table 4 presents the combined impacts of temperature mean and variability, capturing household responses under extreme climate conditions. This approach allows us to identify patterns that are not observable when examining average effects alone.

In summer, the combined effects for lower-income households are uniformly small and statistically insignificant at every temperature configuration: energy moves from 0.041 at the most stable conditions to -0.007 at the most extreme, and food from -0.003 to 0.043, but none of these is distinguishable from zero. We therefore read the summer panel as showing no robust combined response rather than a meaningful reallocation, consistent with the null summer pattern documented in Section 5.1. Higher-income households show a similarly muted summer profile. All of their summer combined effects are statistically insignificant, and food spending shows no reliable change. The summer panel therefore offers no evidence of a meaningful energy–food trade-off for either income group.

Winter conditions present the clear, significant pattern. For lower-income households, the most stable winter conditions already trigger a pronounced trade-off, with increased energy spending (0.076) and food consumption cuts (-0.064). As winter conditions become most extreme, the energy increase persists (0.028) while the food reduction shrinks sharply toward zero and is no longer statistically significant (-0.003), indicating a threshold beyond which these households resist further sacrifices in nutrition, even at the expense of heating.

Higher-income households raise energy spending under both the most stable (0.031) and the most extreme (0.016) winter conditions, with no significant change in food spending in either case. Their ability to maintain essential consumption despite compounded winter stress highlights the protective role of economic resources and structural advantages. Figure 2 summarizes the seasonal marginal effects by income group, confirming that the trade-off binds in winter but not in summer.

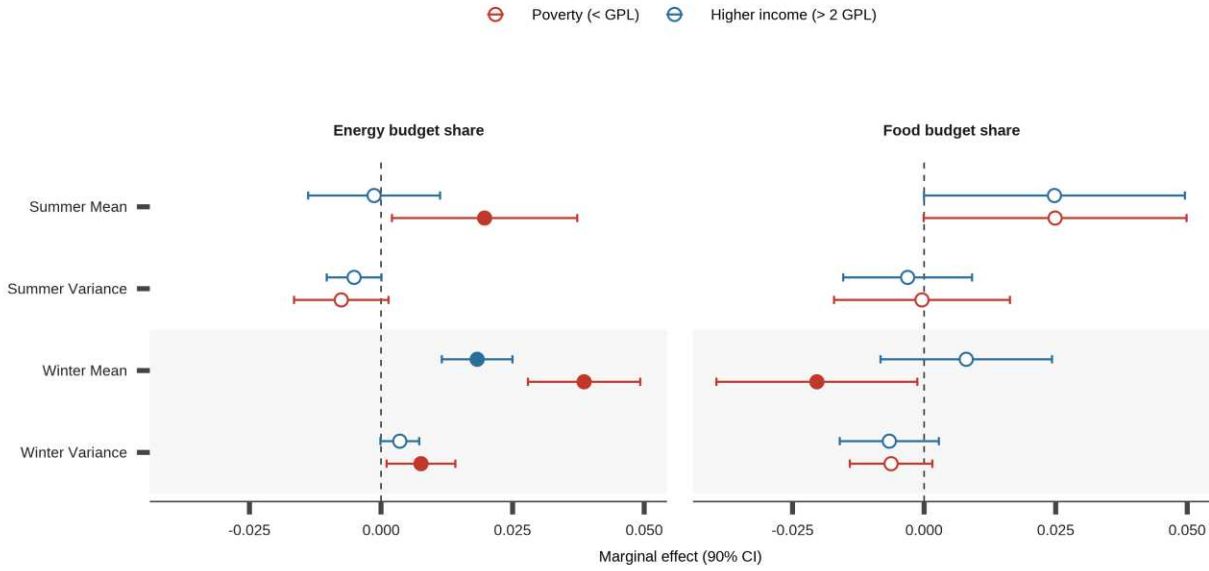


Fig. 2 Seasonal marginal effects by income group: winter binds, summer does not

Note: Survey-weighted marginal effects at the mean for the four temperature moments (summer mean, summer variance, winter mean, winter variance) on the energy (left) and food (right) budget shares, by income group. Points are point estimates and horizontal bars are 90% confidence intervals based on si-gun-gu cluster-robust standard errors. Filled markers are significant at the 10% level; hollow markers are not. Shaded rows denote winter. Red denotes lower-income households (< GPL); blue denotes higher-income households (> 2 GPL). In winter the effects display the heat-or-eat asymmetry—lower-income households cut food while higher-income households do not—whereas in summer most effects are statistically indistinguishable from zero for both groups.

Overall, the combined effects reveal that climate vulnerability is not only income-differentiated but also non-linear. Extreme conditions amplify consumption trade-offs among lower-income groups, but households adjust in complex ways that depend on the interaction between temperature levels and variability. These findings underscore the need for integrated policy responses that address both predictable seasonal risks and the added strain of climate instability.

Table 4 Combined Marginal Effects of Temperatures

	Poverty ("under GPL")				Higher income ("2 GPL")			
	Energy		Food		Energy		Food	
	Min	Max	Min	Max	Min	Max	Min	Max
Summer	0.041 [‡]	-0.007 [‡]	-0.003 [‡]	0.043 [‡]	0.018 [‡]	-0.023 [‡]	0.007 [‡]	0.031 [‡]
Winter	0.076	0.028	-0.064	-0.003 [‡]	0.031	0.016	-0.013 [‡]	0.010 [‡]

Notes: 'Min' represents the combined marginal effects at the minimum values of both temperature mean and variance, while 'Max' represents the combined marginal effects at their maximum values. [‡] denotes statistically insignificant results.

6. Conclusions

This study investigates how household energy and food budget shares respond to seasonal temperature mean and variability across the income distribution in South Korea, using survey-weighted fractional probit models with standard errors clustered at the district level. The central finding is a robust, income-differentiated winter trade-off: as winters turn colder, lower-income households raise their energy budget share and cut their food share—the “heat-or-eat” margin—while higher-income households raise energy spending without sacrificing food. Summer, by contrast, produces no comparable trade-off for either group, so the squeeze on essential consumption is specific to winter rather than a generic response to temperature.

These findings speak directly to the four questions that motivated the paper. First, by making the energy–food margin the explicit object of analysis, we show that a seasonal heat-or-eat trade-off is real but confined to winter. Second, modelling the mean and variance of seasonal temperature jointly reveals that variability matters alongside the level, though its winter role reinforces rather than offsets the mean. Third, estimating the mean-by-variance interaction directly uncovers a threshold: among lower-income households, the most extreme winters cap the heating response and halt further food cuts, a non-linearity that mean-only models would miss. Fourth, and most central, treating the margin as a question of consumption inequality shows that identical weather produces a binding trade-off for poor households and none for richer ones. On the symmetric “cool-or-eat” question raised in the literature, we find no evidence of an analogous summer reallocation in this setting.

Lower-income households face structural constraints that limit their ability to fund heating and nutrition simultaneously when winters turn cold, and they meet the shortfall by reallocating away from food. The winter energy response is precisely estimated; the accompanying food reduction is robust in direction but estimated less precisely (significant at the 10% level) under district clustering. Higher-income households, by contrast, raise winter energy spending without reducing food, underscoring the protective role of financial resources and structural advantages such as energy-efficient housing. The gap between these two responses is the paper’s core message: identical weather produces a binding trade-off for poor households and none for richer ones. This asymmetry is not an artifact of the estimator or the clustering level: it survives a within-household specification with household and year fixed effects and a wild cluster bootstrap at the coarse si-do level (Appendix D).

These results carry important policy implications. First, support should be season-specific. Because the binding trade-off is concentrated in winter, the highest-value interventions are direct winter heating and food assistance for lower-income households. A framework that prioritizes winter heating and food support, while treating summer as a lower-priority period for this particular trade-off, dominates uniform, one-size-fits-all approaches.

Second, because the trade-off appears to be driven by the cost of heating rather than by income alone, targeting on income thresholds may be incomplete. Although our data do not directly measure housing energy efficiency, the heating-cost mechanism implies that two households with similar incomes can face very different winter energy burdens depending on housing quality and heating efficiency. Incorporating indicators such as housing energy

efficiency and energy burden into eligibility criteria, alongside income, could help direct assistance to households most exposed to the heat-or-eat margin. Testing this directly would require data on dwelling characteristics that our sample does not contain, and we flag it as a priority for future work.

Third, energy assistance and food assistance could be linked more explicitly. Our results show that the cost of maintaining adequate heating shapes food spending under cold stress, so the two margins are connected at the household level even though support programs typically operate on separate tracks. In Korea, the main energy and food transfers—the Energy Voucher and the Agri-food Voucher—are both means-tested on the same basic-livelihood-security base and share common welfare portals, so the income-based structure already provides a partial bridge between them. The bridge is only partial, however: the two programs are administered by different ministries and differ in scope—the Agri-food Voucher is restricted to households receiving the Livelihood Benefit (the lowest tier of the National Basic Livelihood Security system) with children or a pregnant member, a narrower pool than the Energy Voucher's—so their recipient populations overlap only in part, and no mechanism explicitly coordinates the two for the same household. The value added would therefore come less from creating a new program than from coordinating the existing ones—for example, aligning winter energy support with food assistance for the same households—and from pairing transfers with structural measures such as energy-efficiency upgrades.

While this study focuses on South Korea, the pattern—an income-differentiated winter trade-off between heating and food, absent in summer—may speak to other high-income societies exposed to energy-price volatility and widening consumption inequality, particularly those with aging populations and cold winters. We did not test age heterogeneity directly, so this extension is suggestive; with that caveat, the lessons for seasonally responsive transfers, housing energy-efficiency policy, and the closer coordination of energy and food assistance plausibly travel to comparable settings.

Several limitations should be acknowledged. First, the analysis relies on expenditure shares rather than direct measures of well-being, health, or nutritional status, so the welfare implications are inferred rather than observed. Second, the summer channel as a whole is weak in our estimates: aside from a marginal energy response among lower-income households, the summer mean, variance, and their combined effects are largely indistinguishable from zero once standard errors are clustered at the district level, so we treat the summer results as a contrast to winter rather than as evidence of a summer trade-off. Third, the study focuses on temperature; other climate risks, such as precipitation extremes or compound weather events, may also affect household budgets and deserve further investigation. Finally, the baseline model identifies the temperature effects partly from cross-district variation, controlling for climate region rather than for each household; we therefore verify in Appendix D that the winter trade-off persists under within-household estimation, which mitigates concern about time-invariant district confounders.

Future research should build on these findings by incorporating health and nutrition outcomes into assessments of climate vulnerability and by evaluating the effectiveness of integrated welfare programs in reducing trade-offs under real-world climate stress. Additionally, exploring how seasonally differentiated support mechanisms, structural housing interventions, and targeted energy-efficiency upgrades modify household vulnerability can provide more actionable insights for policy design in increasingly unstable climate environments.

Declarations

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Author contributions: All authors contributed to the study conception and design. Data collection and analysis were performed by Cherry Kim. The first draft of the manuscript was written by Cherry Kim, and both authors commented on previous versions. Both authors read and approved the final manuscript.

Data availability: The household data analyzed in this study are from the Korean Labor and Income Panel Study (KLIPS), administered by the Korea Labor Institute, and are available from the KLIPS data repository (<https://www.kli.re.kr/klips>) upon registration. Daily temperature data are publicly available from the Korea Meteorological Administration (KMA). Price data are publicly available from Statistics Korea (KOSTAT). Restrictions apply to the redistribution of the KLIPS microdata, which were used under the data provider's terms.

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Appendix A: Overview of South Korea's energy Infrastructure and Pricing System

The residential cooling and heating landscape in South Korea involves multiple entities and energy sources, all under government supervision. The key player in this system is the Korea Gas Corporation (KOGAS), a publicly owned natural gas company and the sole importer and wholesale supplier of liquefied natural gas (LNG) in the country, except for some direct imports by private-sector firms. KOGAS imports natural gas from the global market, including countries like Australia, Qatar, and the U.S., and distributes it for two main purposes: power generation and city gas for heating (IEA, 2023).

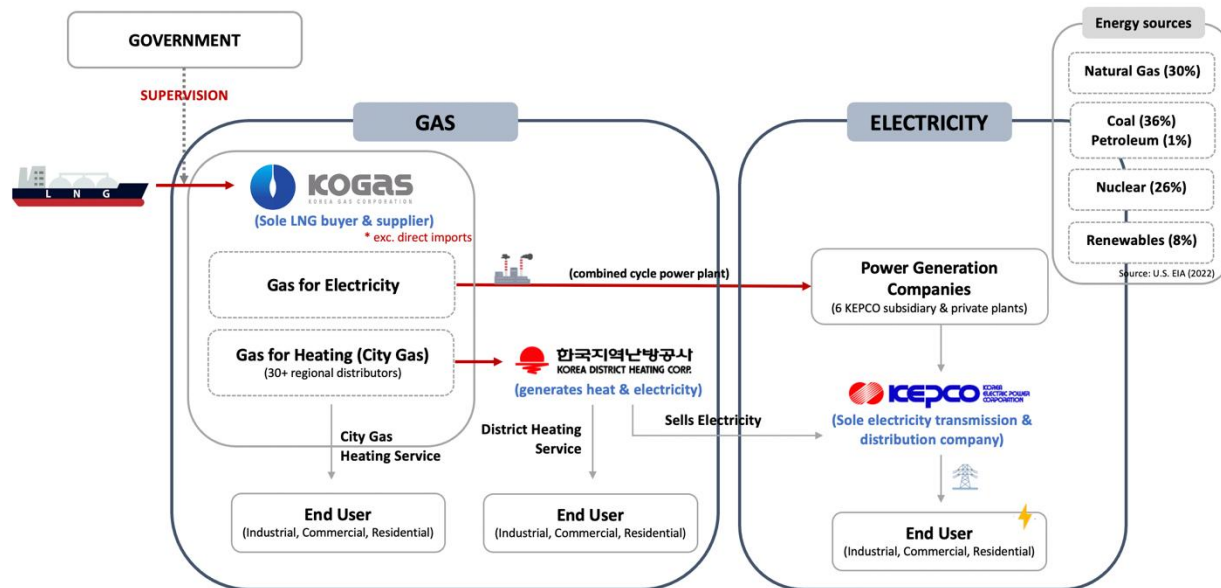
For electricity generation, KOGAS supplies LNG to power generation companies, including six subsidiaries of the Korea Electric Power Corporation (KEPCO) and private plants. Despite the presence of multiple power generation entities, KEPCO remains the sole company responsible for the transmission and distribution of electricity across South Korea. This means that all electricity generated, regardless of the source, is eventually transmitted and distributed to end-users—industrial, commercial, and residential—by KEPCO. The energy sources in South Korea for electricity generation include natural gas (30%), coal (36%), petroleum (1%), nuclear (26%), and renewables (8%) (U.S. EIA, 2023). This diversity is essential for maintaining a stable energy supply, particularly during peak demand periods in summer and winter when the need for cooling and heating surges.

On the heating side, KOGAS supplies natural gas to city gas companies (private for-profit corporations) that exclusively supply heating directly to end-users, encompassing industrial, commercial, and residential sectors. Additionally, the Korea District Heating Corporation (KDHC) purchases natural gas from KOGAS to generate both heat and electricity at its plants. The heat generated is then used for district heating services, which are provided to a similar range of end-users. Moreover, KDHC supplies the electricity it generates to KEPCO, integrating its operations into the broader national grid.

Overall, this intricate system of energy procurement, distribution, and consumption highlights the interconnected nature of South Korea's energy infrastructure. The government's regulatory oversight ensures stability in energy prices and supply, even as energy supply companies navigate financial challenges due to regulated pricing structures. This regulatory environment is crucial, especially for low-income households that rely heavily on affordable energy for heating during harsh summer and winter months. Understanding this framework is vital for assessing how households manage their energy and food budgets in response to climate change.

By maintaining a diverse energy portfolio and regulatory oversight, South Korea aims to ensure a stable and affordable energy supply, which is particularly important for vulnerable populations. This background sets the stage for understanding the broader implications of energy consumption patterns and the trade-offs households make in response to varying temperature conditions.

Figure 3 provides an overview of South Korea's residential energy system, tracing the flow of natural gas and electricity from importation to end-users and the roles of KOGAS, KEPCO, and KDHC.



Source: Own elaboration

Fig. 3 Overview of South Korea's Residential Energy System

Note: This diagram illustrates the flow of natural gas and electricity from importation to end-users, highlighting the roles of KOGAS, KEPCO, and the Korea District Heating Corporation (KDHC). The energy mix for electricity generation is also depicted, with sources including natural gas, coal, petroleum, nuclear, and renewables.

Appendix B. Full Regression Results

Table A1. Full Regression Results (with controls)

		Total		Poverty ("under GPL")		Higher Income ("2 times GPL")	
		Energy	Food	Energy	Food	Energy	Food
γ_1	Summer mean (T_μ^s)	0.015 (0.013)	-0.002 (0.025)	0.038* (0.022)	0.007 (0.029)	0.014 (0.012)	0.015 (0.030)
γ_2	Summer variance (T_σ^s)	0.021 (0.029)	-0.073 (0.049)	0.050 (0.045)	-0.057 (0.060)	0.044 (0.033)	-0.033 (0.060)
γ_3	Winter mean (T_μ^{w*})	0.036*** (0.008)	-0.023 (0.015)	0.061*** (0.012)	-0.048** (0.019)	0.025*** (0.007)	-0.003 (0.017)
γ_4	Winter variance (T_σ^w)	0.005** (0.002)	-0.004 (0.004)	0.006 (0.004)	-0.004 (0.005)	0.003 (0.002)	-0.006 (0.006)
γ_5	$T_\mu^s \times T_\sigma^s$	-0.001 (0.001)	0.003 (0.002)	-0.002 (0.002)	0.002 (0.003)	-0.002 (0.001)	0.001 (0.003)
γ_6	$T_\mu^{w*} \times T_\sigma^w$	-0.001** (0.000)	0.001* (0.001)	-0.002*** (0.001)	0.003** (0.001)	-0.001 (0.000)	0.001 (0.001)
δ	Δ price	0.017 (0.010)	0.009 (0.007)	0.022 (0.018)	0.006 (0.009)	0.009 (0.010)	0.005 (0.007)
θ	Income (1K KRW)	-0.013*** (0.002)	-0.011*** (0.001)	-0.052*** (0.009)	-0.042*** (0.012)	-0.004*** (0.001)	-0.006*** (0.001)
ζ	Household size	-0.063*** (0.004)	-0.024*** (0.004)	-0.055*** (0.008)	-0.011 (0.010)	-0.057*** (0.004)	-0.027*** (0.005)
	HH age over 65	0.121*** (0.010)	0.073*** (0.011)	0.104*** (0.017)	0.039* (0.021)	0.071*** (0.017)	0.072*** (0.017)
<i>Education</i>							
	Secondary	-0.039*** (0.009)	-0.058*** (0.011)	-0.003 (0.015)	-0.049*** (0.018)	-0.017 (0.013)	-0.056*** (0.015)
	Tertiary	-0.045*** (0.012)	-0.066*** (0.013)	-0.027 (0.027)	-0.069*** (0.024)	-0.023 (0.015)	-0.051*** (0.018)
<i>Tenure status</i>							
	Long-term lease	0.003 (0.009)	-	0.010 (0.022)	-	-0.004 (0.009)	-
	Rent	-0.223*** (0.014)	-	-0.250*** (0.021)	-	-0.199*** (0.014)	-

Constant	-1.469*** (0.321)	-0.345 (0.622)	-1.955*** (0.527)	-0.477 (0.696)	-1.549*** (0.290)	-0.784 (0.743)
Year & region FE	Yes	Yes	Yes	Yes	Yes	Yes
N	23,562	23,562	6,851	6,851	10,551	10,551
Pseudo R ²	0.320	0.128	0.206	0.072	0.176	0.061
Clusters (si-gun-gu)	218	218	206	206	199	199

Notes: Estimates from survey-weighted fractional probit models (quasi-binomial GLM, probit link) using the KLIPS 09-integrated-sample household longitudinal weight. Standard errors (in parentheses) are clustered at the si-gun-gu (district) level (218 clusters). The dependent variable is the budget share of household expenditure on the indicated spending category. All models include year and region fixed effects and the controls described in Section 3.2. *p<0.1, **p<0.05, ***p<0.01. Tenure status (long-term lease, rent) is included only in the energy-share models, since housing tenure directly affects home energy costs but is not theoretically linked to food spending.

Appendix C. Combined Marginal Effects under Stable versus Extreme Conditions

Figure 4 depicts the combined marginal effects under stable versus extreme conditions for winter and summer.

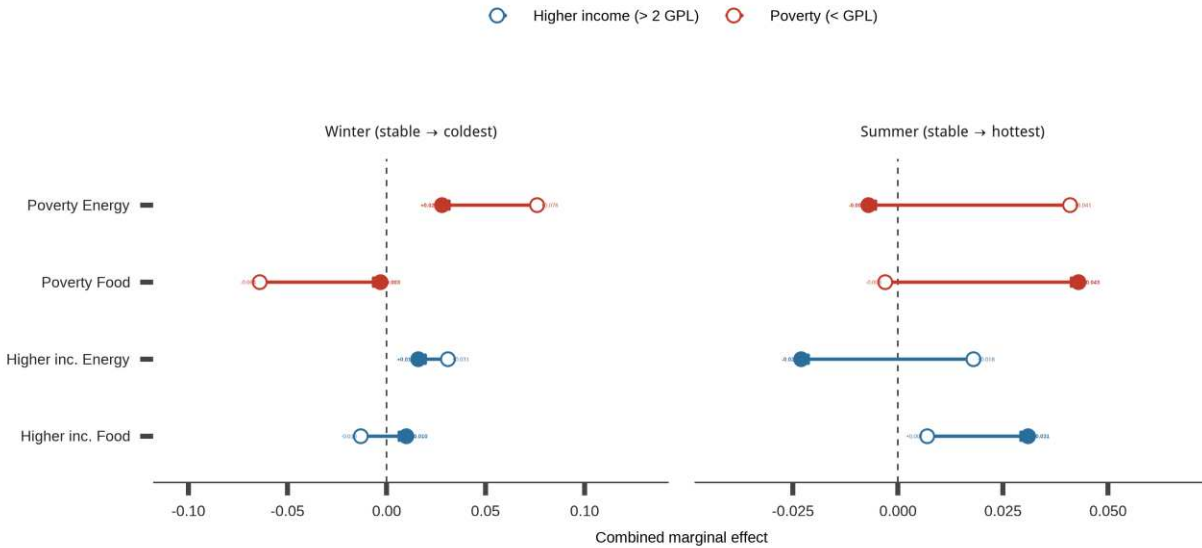


Fig. 4 From stable to extreme conditions: combined marginal effects

Note: Combined marginal effects of temperature mean and variance on the energy and food budget shares, evaluated at the most stable (minimum) and most extreme (maximum) temperature conditions, for winter (left) and summer (right). Hollow markers denote stable (minimum) conditions and filled markers denote extreme (maximum) conditions; arrows trace the movement from stable to extreme. Red denotes lower-income households (< GPL); blue denotes higher-income households (> 2 GPL). In winter, lower-income households' food reduction attenuates as conditions become more extreme (from -0.064 toward a statistically insignificant -0.003), consistent with a threshold beyond which nutrition is no longer reduced, while higher-income households show smaller movements. Summer displays no consistent pattern. Values correspond to Table 4.

Appendix D. Robustness: Within-Household Estimation and Few-Cluster Inference

This appendix reports two checks on the winter result. Table A2 replaces the baseline specification with a linear probability model that adds household and year fixed effects, so the temperature coefficients are identified from within-household variation over time rather than from cross-district differences. Table A3 reports a restricted wild cluster bootstrap (Rademacher weights, $B = 9,999$) for the key winter coefficients, clustering at the coarse si-do level (sixteen clusters) where the usual cluster-robust asymptotics are unreliable. Standard errors in Table A2 are clustered at the si-gun-gu level.

[Insert Table A2 here]

Table A2. Household fixed-effects LPM (within household + year FE)

Group / dependent variable	Winter mean	Winter variance
Poverty — Energy share	0.0056** (0.0026)	0.0003 (0.0006)
Poverty — Food share	-0.0078* (0.0041)	-0.0002 (0.0011)
Higher income — Energy share	0.0005 (0.0012)	0.0002 (0.0003)
Higher income — Food share	-0.0055 (0.0049)	0.0003 (0.0015)

Notes: Coefficients (cluster-robust SE at si-gun-gu in parentheses) from a linear probability model with household and year fixed effects; identification is from within-household variation. Poverty: $N = 6,217$, 1,840 households, 200 clusters. Higher income: $N = 9,894$, 3,053 households, 195 clusters. The winter heat-or-eat pattern is preserved among lower-income households, while higher-income households show no significant food response. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Because conventional cluster-robust inference is unreliable with only sixteen si-do clusters, we assess the winter coefficients with a restricted wild cluster bootstrap. All three remain significant, confirming that the winter heat-or-eat pattern is not an artifact of the clustering level.

[Insert Table A3 here]

Table A3. Wild cluster bootstrap at si-do (16 clusters), restricted, $B = 9,999$

Winter coefficient (LPM)	Coef. (si-do SE)	Bootstrap p
Poverty, winter mean → Energy share	0.012 (0.004)	0.012
Poverty, winter mean → Food share	-0.016 (0.007)	0.077
Higher income, winter mean → Energy share	0.004 (0.001)	0.021

Notes: Restricted wild cluster bootstrap (Rademacher weights) for the winter-mean coefficient of a linear probability model, clustering at the si-do level (sixteen clusters). Coefficients with si-do cluster-robust standard errors in parentheses; the bootstrap p-value is the two-sided value from $B = 9,999$ replications.